# Impact of JPEG2000 compression in correlation algorithms. Is subsampling a better compression strategy?

G. Blanchet * A. Buades† B. Coll ‡ J.M. Morel§
B. Rougé ¶

**Abstract**

## 1 Introduction

The main motivation of this paper is to analyze the impact of jpeg compression quantitatively. That is, how does compression affects the ability of measuring and comparing features in the image? A majority of processing and analyzing image techniques are based in comparing different pixel values, selected feature or entire patches in the image. These comparisons are even more important when dealing with image sequences or stereo pairs. When estimating motion or depth, the comparison of characteristic features or entire patches are of major importance.

However, most studies interested in the evaluation of jpeg compression algorithms consider the visual quality of the compressed image as the unique criterium. Visual quality is very difficult to measure and remains a subjective evaluation. For example, in [5, 6, 7] the authors study the rate of compression acceptable for different medical imaging techniques. Their conclusion is that a compression of a factor 10 yields a good visual quality but superior rates of compression quickly degrades the image. Other studies like [9, 10] concentrate on technical aspects of the codification and transmission evaluating the simplicity, the completeness or transmission speed of different jpeg algorithms.

In remote sensing a similar study to the one performed in medical imaging was performed in [12] dealing with stereo pairs. The conclusion was the same

*CNES, 18 avenue Edouard Belin, Toulouse 31401, France
†MAP5, CNRS - Université Paris Descartes, Paris, France.
‡Dpt Matematiques i Informatica, Universitat Illes Balears, Spain
§Centre de Mathématiques et de Leurs Applications, École Normale Supérieure de Cachan, France.
¶CESBIO, 18 Av E. Belin, Toulouse 31400, France

that for medical images asserting that a compression factor of ten was optimal. In [11] the authors include the perceived depth, perceived sharpness and perceived eye-strain in the study. This work includes studies on symmetric or asymmetric compression.

The rest of evaluation or comparison papers on jpeg compression refer to specific applications as the classification in satellite imaging [14, 8]. These approaches rely on complex classification algorithms which are not able to generally quantify the impact of compression in images.

We will maintain our interest in satellite imaging and the stereo correspondence problem. First, because resolution in satellite imaging is very large compared to most image techniques. Thus, compression is an avoidable step prior to transmission to ground. Second, stereo correspondence is still a central problem problem in satellite imaging and its objective is to locate similar features or entire patches in each image of the pair. For this reason, we will concentrate on correlation algorithms for recovering the disparity map between a stereo pair. Even if we focus in a particular application, correlation algorithms consist in finding for each image patch of a reference image the most similar in a second image. This is the basic step in many video processing techniques as filtering, motion estimation or tracking. Recently, the comparison of image patches have become a widely used processing technique for still image applications like denoising, texture synthesis, superresolution, etc.

The jpeg2000 compression algorithm as the classical jpeg algorithm have two main drawbacks, they are not translation invariant and do not modify image noise in a coherent manner [2, 4]. For this reason, we shall compare the jpeg compression algorithm with a linear convolution plus subsampling strategy. We will show that the clear lose in high frequency information due to the linear filtering is compensated by the non presence of artifacts, the translation invariance and the noise reduction. Thus, a superior accuracy in disparity estimation is obtained by the subsampling strategy.

## 2 Impact of jpeg compression in the computation of a disparity map

The evaluation of the attained accuracy when applying a correlation algorithm between a stereo pair needs a perfect and perfectly registered ground truth disparity image. In most cases, this ground truth is not available or its precision is not high enough to permit the type of tests we want to carry out in this paper. In addition, the disparity computation itself is a difficult problem not solved yet. Any stereo computation algorithm has its drawbacks and may not work in all cases. For classical correlation algorithms do not manage occlusions and suffer of the so called adhesion artifacts, namely, the fact that image patches contain features of different depths (see [3] for more details and mathematical discussion). In order to keep a simple algorithm and be able to evaluate the accuracy, we decided to directly translate one reference image in the horizontal direction and thus the epipolar line. In such a way, we eliminate the drawbacks of stereo algorithms and we can concentrate in the ability of finding the same patches.

The overall chain takes a reference image and applies a pixel or subpixel translation to the whole image. Both images are compressed to a fixed rate and white noise of fixed standard deviation is added. For each pixel of the reference image, a squared neighborhood window around is taken and looked for the closest one in the second image in the same horizontal line and close to the original position. The distances between the window in the first image and windows centered at pixel positions in the second image are interpolated in order to get a subpixelian estimate for the disparity (see [3] for more details).

The first experience testing the impact of compression in accuracy of disparity estimation is carried out on a full database of texture images (see figure 1). These texture images have size 256x256 pixels and are coded in 8 bits. Each image of this data set is translated of an integer factor, 3, and a non integer factor, 3.7 and compressed to a fixed rate by using the compression software Kakadu [1]. This software allows to fix the exact average bit rate of the compressed image. Table 1 displays the average errors in the disparity map over the whole image set for different rates of compression and signal to noise ratios. Several important observations can be easily derived from this table. First, the error committed is quite similar when an integer or non integer translation is applied. Second, as expected, the error increases when the number of bits per pixel decreases or the noise standard deviation increases. In the most advantageous case of nearly no compression (4 bits per pixel) and a noise standard deviation of 1 the mean error committed by jpeg2000 compression is 0.03 pixels, that we get a high accuracy result. However, by increasing the ratio of compression to 1 bit per pixel and adding a white noise of standard deviation 2, which are still highly reasonable, the error is increased to 0.2 pixels. That is, the accuracy of the computed disparity is quickly degraded.

One explanation to this fast degradation on the jpeg accuracy could be the fact that images in the database are highly textured and thus very difficult to compress. For this reason, we also applied the same process to two real satellite images of different resolutions, figures 2 and 3. For these images, the same fast degradation is observed and errors are similar or slightly worse than for the database experience (see tables 2 and 4). More detailed discussion on this experiences is left for the last section.

# 3 Subsampling as a compression algorithm

The proposed strategy follows from several observations about compression and disparity computation. First, zones of images with a constant depth or altitude are related from one to the other image of the pair by a translation. As, we want to identify the corresponding points in both images we would like our compression algorithm to be translation invariant. Second, it is clear that any lossy compression algorithm will filter in some way the noise. We would like to control the manner how noise is transformed by the compression algorithm. That is, we still prefer a white noise than a correlated noise or its transformation into artifacts.

From the above discussion, we shall conclude that the only compression algorithm that satisfies above conditions is the linear filtering by convolution with a Gaussian kernel. We can argue that Gaussian convolution is a compression algorithm since it reduces the spectral information of the image. Furthermore, this spectral reduction allows for a spatial subsampling, with a subsampling factor depending on the kernel standard deviation and limited by aliasing.

In this paper, we shall test subsampling factors of two and three, with corresponding gaussian standard deviations of 1.2 and 1.8. This subsampling reduces the amount of pixels in the image by a factor 4 or 9, leading to a compression rate of 2 and 0.88 bits respectively. Subsampled images can still be compressed by any standard lossless image compression algorithm. State of the art lossless algorithms achieve a compression factor of more than two [13]. Thus, the final compression rate of a two and three subsampling respectively are 1 and 0.44 bits per pixel. Quantified wavelet coefficients are already coded in a lossless manner, and therefore cannot be still compressed by a lossless algorithm.

Subsampled pairs are zoomed by zero padding before computing the disparity map. The objective is to obtain a disparity map with the same resolution than the one obtained by compression. Even if we could think that the lose of high frequency information of the zoomed image would affect much more the quality of the estimated depth than the compression, it must be noted that the zoomed image is artifact free and contains much less noise than the high resolution image.

# 4 Discussion

In this section we proceed with the evaluation and comparison of the jpeg and subsampling strategies. We will evaluate the degradation of processed pairs for different ratios of compression and noise standard deviation with images of figures 1, 2 and 3. Figure 1 contain the set of textures we used in previous section to evaluate the jpeg2000 compression algorithms. Image in figure 2 is an aerial urbain image of resolution 50cm. The satellite image of figure 3 contains more flat zones and even saturated shadow zones that makes it more compressible for a JPEG algorithm. The image contains many shadows where there's no information to match, we have removed these dark zones when computing the error of the disparity map (the mask showing the eliminated zones is displayed in Figure 3).

Tables 1, 2 and 4 compare the accuracy on the disparity when compression or subsampling are applied in the different pairs. The tables display the error between the computed disparity and the ground truth constant displacement, measured in pixels. From all tables, we observe that for both the compression and subsampling strategies the error increases when the number of bits per pixel decreases or the noise standard deviation increases. We also observe that with

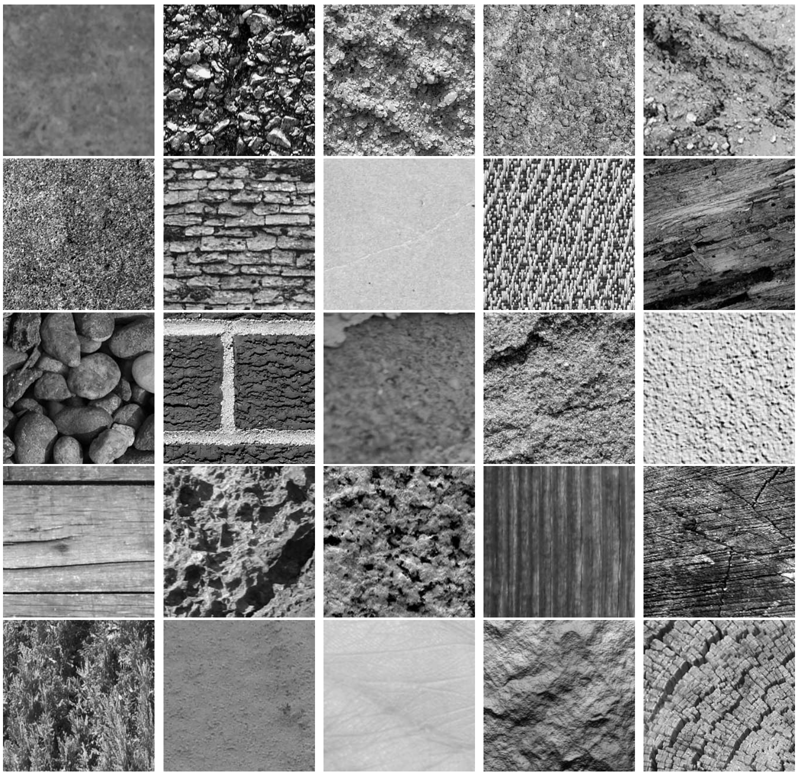

Figure 1: Texture images data set.

the same ratio of compression the error obtained by the proposed strategy is lower than for the JPEG compression algorithm. The error committed for the proposed algorithm with a subsampling of factor 2 (1 bit per pixel) is similar to the one obtained with JPEG compression with 3 bits per pixel. The error committed for the proposed algorithm with a subsampling of factor 3 (0.44 bits per pixel) is similar to the one obtained with JPEG compression with 2 bits per pixel.

The reader may argue that the processed pair with the subsampling strategy has been previously convolved and therefore the zoomed pair used as input for the correlation algorithm is less noisy. This is absolutely correct and for this reason we repeated the experiences by applying a convolution of standard deviation 1.2 (the same used for the subsampling of factor 2) to the JPEG compressed images before applying the correlation algorithm. These values are illustrated in the same tables 1, 2 and 4 . The accuracy values obtained with the convolution are similar to the original errors and accuracy is not improved. The convolution is not able to remove the created artifacts or recover the original patterns. Some of the textures (even in the satellite images) actually behave like a white noise and wavelet coefficients quantified to zero enhance neighboring

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.037 | 0.082 | 0.131 | 0.231 | 0.493 | 0.067 | 0.083 |
| $\sigma = 2$ | 0.067 | 0.111 | 0.158 | 0.256 | 0.511 | 0.096 | 0.126 |
| $\sigma = 4$ | 0.169 | 0.212 | 0.240 | 0.336 | 0.570 | 0.169 | 0.215 |

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.035 | 0.071 | 0.102 | 0.160 | 0.331 | 0.053 | 0.123 |
| $\sigma = 2$ | 0.066 | 0.101 | 0.129 | 0.189 | 0.358 | 0.083 | 0.153 |
| $\sigma = 4$ | 0.177 | 0.209 | 0.227 | 0.288 | 0.448 | 0.159 | 0.234 |

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.055 | 0.106 | 0.137 | 0.225 | 0.422 | 0.053 | 0.123 |
| $\sigma = 2$ | 0.085 | 0.133 | 0.165 | 0.249 | 0.445 | 0.083 | 0.153 |
| $\sigma = 4$ | 0.160 | 0.211 | 0.236 | 0.318 | 0.504 | 0.159 | 0.234 |

Table 1: Mean average error in pixels on the image data set of figure 1. The rate columns indicate the number of bits per pixel chosen in the JPEG compressor. For the two last columns we show the mean error obtained with the proposed strategy, denoted by ss2 and ss3, which means subsampling of order two and three, respectively. The first table displays the mean error for an integer translation and the second one for a non-integer translation. The results are quite similar. In the last table, we applied a gaussian convolution to the compressed JPEG images before applying the correlation algorithm (see the text for more details).

wavelet coefficients which are not canceled leading to the well known wavelet outliers (see [2] for an analysis of artifacts when wavelet thresholding is applied to pure noise images).

Because of the superior accuracy obtained with the subsampling algorithm compare to the jpeg 2000, we decide to carry out the same comparison with the classical DCT jpeg algorithm. The process was exactly the same except for the compression step where a classical jpeg compression algorithm was used. The accuracy for those experiences is displayed in tables 5 and 3 and are slightly worse to the ones obtained with the jpeg2000 algorithm.

# References


[1] Kakadu Sofware. *http://www.kakadusoftware.com/*.

[2] A. Buades, B. Coll, and J.M. Morel. Nonlocal image and movie denoising. *International Journal of Computer Vision*, 76(2):123–139, 2008.

[3] J. Delon and B. Rougé. Small baseline stereovision. *Journal of Mathematical Imaging and Vision*, 28(3):209–223, 2007.

Figure 2: Satellite urban image provided by the french spatial agency, CNES. The resolution of this image is 50cm. Impact of compression and subsampling in disparity accuracy for this image are displayed in table 2.


[4] DL Donoho. De-noising by soft-thresholding. *Information Theory, IEEE Transactions on*, 41(3):613–627, 1995.

[5] F. Ebrahimi, M. Chamik, and S. Winkler. JPEG vs. JPEG2000: An objective comparison of image encoding quality. In *Proc. of SPIE*, volume 5558, pages 300–308, 2004.

[6] A. Kalyanpur, V.P. Neklesa, C.R. Taylor, A.R. Daftary, and J.A. Brink. Evaluation of JPEG and Wavelet Compression of Body CT Images for Direct Digital Teleradiologic Transmission1. *Radiology*, 217(3):772, 2000.

[7] A. Khademi and S. Krishnan. Comparison of JPEG 2000 and Other Lossless Compression Schemes for Digital Mammograms. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pages 3771–3774, 2005.

[8] Zhai Liang, Tang Xinming, Zhang Guo, and Wu Xiaoliang. Effects of jpeg2000 and spiht compression on image classification. In *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences Conference, Beijing 2008*, Aug 2008.

[9] M. Rhepp, H. Stogner, and A. Uhl. Comparison of JPEG and JPEG 2000 in low-power confidential image transmission. In *Proceedings (CD-ROM) of the European Signal Processing Conference, EUSIPCO*, volume 4. Citeseer.

[10] D. Santa-Cruz, R. Grosbois, and T. Ebrahimi. JPEG 2000 performance evaluation and assessment. *Signal Processing: Image Communication*, 17(1):113–130, 2002.

[11] P. Seuntiens, L. Meesters, and W. Ijsselsteijn. Perceived quality of compressed stereoscopic images: Effects of symmetric and asymmetric JPEG

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.194 | 0.231 | 0.312 | 0.400 | 0.580 | 0.165 | 0.207 |
| $\sigma = 2$ | 0.327 | 0.361 | 0.344 | 0.423 | 0.586 | 0.246 | 0.251 |
| $\sigma = 4$ | 0.488 | 0.494 | 0.491 | 0.490 | 0.609 | 0.363 | 0.358 |

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.177 | 0.219 | 0.293 | 0.377 | 0.544 | 0.165 | 0.207 |
| $\sigma = 2$ | 0.255 | 0.302 | 0.321 | 0.400 | 0.551 | 0.246 | 0.251 |
| $\sigma = 4$ | 0.370 | 0.401 | 0.404 | 0.460 | 0.583 | 0.363 | 0.358 |

Table 2: Mean error on the disparity on the image in figure 2. The image is translated in the horizontal direction. The rate columns indicate the number of bits per pixel chosen in the JPEG compressor. For the two last columns we show the mean error obtained with the proposed strategy, denoted by ss2 and ss3, which means subsampling of order two and three, respectively. In the second table, we applied a gaussian convolution to the compressed JPEG images before applying the correlation algorithm (see the text for more details).

coding and camera separation. *ACM Transactions on Applied Perception (TAP)*, 3(2):109, 2006.

[12] T. Tada, K. Cho, H. Shimoda, T. Sakata, and S. Sobue. An evaluation of jpeg compression for on-line satellite images transmission. In *Geoscience and Remote Sensing Symposium, 1993. IGARSS '93. Better Understanding of Earth Environment., International*, pages 1515–1518 vol.3, Aug 1993.

[13] MJ Weinberger, G. Seroussi, and G. Sapiro. The LOCO-I lossless image compression algorithm: principles andstandardization into JPEG-LS. *IEEE Transactions on Image Processing*, 9(8):1309–1324, 2000.

[14] A. Zabala, X. Pons, R. Díaz-Delgado, F. García, F. Aulí-Llinàs, and J. Serra-Sagristà. Effects of JPEG and JPEG2000 lossy compression on remote sensing image classification for mapping crops and forest areas. In *26th International Geoscience and Remote Sensing Symposium. IEEE Press*, pages 790–793, 2006.

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.345 | 0.428 | 0.453 | 0.519 | 0.688 | 0.165 | 0.207 |
| $\sigma = 2$ | 0.421 | 0.461 | 0.454 | 0.534 | 0.723 | 0.246 | 0.251 |
| $\sigma = 4$ | 0.537 | 0.529 | 0.534 | 0.550 | 0.724 | 0.363 | 0.358 |

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.631 | 0.680 | 0.662 | 0.699 | 0.781 | 0.165 | 0.207 |
| $\sigma = 2$ | 0.636 | 0.627 | 0.685 | 0.666 | 0.749 | 0.246 | 0.251 |
| $\sigma = 4$ | 0.752 | 0.697 | 0.585 | 0.613 | 0.778 | 0.363 | 0.358 |

Table 3: Mean error on the image in figure 2 with DCT classical JPEG. The image is translated in the horizontal direction. The rate columns indicate the number of bits per pixel chosen in the JPEG compressor. For the two last columns we show the mean error obtained with the proposed strategy, denoted by ss2 and ss3, which means subsampling of order two and three, respectively. In the second table, we applied a gaussian convolution to the compressed dct JPEG images before applying the correlation algorithm (see the text for more details).

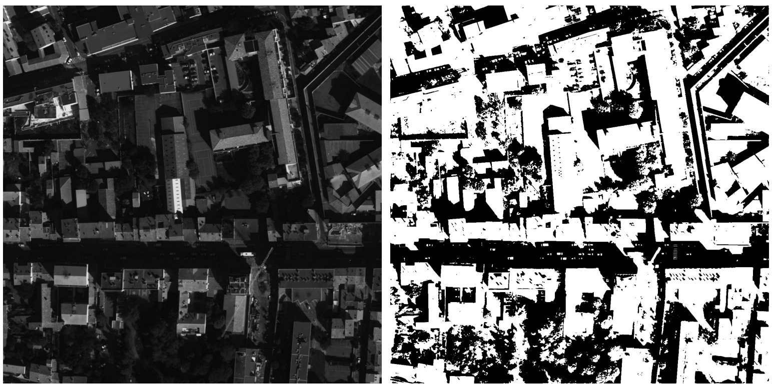

Figure 3: Satellite image of resolution 20 cm. Satellite image of resolution 20cm. Impact of compression and subsampling in disparity accuracy for this image are displayed in table 4.

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.239 | 0.250 | 0.268 | 0.318 | 0.545 | 0.201 | 0.329 |
| $\sigma = 2$ | 0.398 | 0.424 | 0.412 | 0.419 | 0.568 | 0.302 | 0.381 |
| $\sigma = 4$ | 0.661 | 0.693 | 0.667 | 0.655 | 0.652 | 0.465 | 0.501 |

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.209 | 0.216 | 0.243 | 0.283 | 0.492 | 0.201 | 0.329 |
| $\sigma = 2$ | 0.308 | 0.334 | 0.330 | 0.376 | 0.519 | 0.302 | 0.381 |
| $\sigma = 4$ | 0.466 | 0.515 | 0.509 | 0.522 | 0.607 | 0.465 | 0.501 |

Table 4: Mean error on the image in figure 3. This image is taken at 20cm of resolution. The image is translated in the horizontal direction. The rate columns indicate the number of bits per pixel chosen in the JPEG compressor. For the two last columns we show the mean error obtained with the proposed strategy, denoted by ss2 and ss3, which means subsampling of order two and three, respectively. In the second table, we applied a gaussian convolution to the compressed JPEG images before applying the correlation algorithm (see the text for more details).

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.240 | 0.246 | 0.267 | 0.335 | 0.597 | 0.201 | 0.329 |
| $\sigma = 2$ | 0.444 | 0.408 | 0.406 | 0.427 | 0.609 | 0.302 | 0.381 |
| $\sigma = 4$ | 0.723 | 0.693 | 0.648 | 0.637 | 0.712 | 0.465 | 0.501 |

| | 4 b/p | 2 b/p | 1.5 b/p | 1 b/p | 0.5 b/p | ss2 (1 b/p) | ss3 (0.44 b/p) |
|---|---|---|---|---|---|---|---|
| $\sigma = 1$ | 0.176 | 0.223 | 0.239 | 0.303 | 0.519 | 0.201 | 0.329 |
| $\sigma = 2$ | 0.318 | 0.303 | 0.334 | 0.365 | 0.534 | 0.302 | 0.381 |
| $\sigma = 4$ | 0.501 | 0.523 | 0.536 | 0.579 | 0.628 | 0.465 | 0.501 |

Table 5: Mean error on the image in figure 3 and classical DCT JPEG compression. This image is taken at 20cm of resolution. The image is translated in the horizontal direction. The rate columns indicate the number of bits per pixel chosen in the JPEG compressor. For the two last columns we show the mean error obtained with the proposed strategy, denoted by ss2 and ss3, which means subsampling of order two and three, respectively. In the second table, we applied a gaussian convolution to the compressed JPEG images before applying the correlation algorithm (see the text for more details).